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Original Article

How relevant are generalist real estate indices in emerging markets?

Qual é a Relevância de Índices Imobiliários Generalistas em Mercados Emergentes?

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Abstract

Real estate indices often rely on strong constant quality assumptions and are too general to be carefully considered by investors. Hedonic techniques are more rigorous than median-price measures to control for quality of the assets in place and the quality of the assets that are put on the market at different times. This research aims to investigate how these limitations affect the usefulness of indicators available in the Brazilian market and how specialized, technically superior (and relatively easy-to employ), indices can contribute to improve performance measurement in emerging real estate markets. To do this, we use an appraisal-based rent dataset from Sao Paulo to create two types of time-dummy measures for office properties. To our records, there appears to be no studies that cover the recent meltdown in this market in such level of detail or that compare the performance of different time-dummy methods. The first model – *standard* – includes time dummies, submarket dummies and property-specific attributes as controls for building quality. The second – *fixed effect* – is an alternative model, where we consider time dummies, time-varying characteristics and property-specific fixed effects. The latter approach deals with time-unvarying locational and property-specific unobserved heterogeneity. Our results reinforce that obtuse measures available often fail to disentangle specific aspects of real estate cycles, which tend to be quite prominent in emerging real estate markets.

Keywords: Office properties; Hedonic indices; Brazil

Resumo

Os índices imobiliários dependem de hipóteses de qualidade constante. As técnicas hedônicas são mais rigorosas do que preços médios, pois as primeiras controlam a qualidade dos imóveis disponíveis no mercado e a inclusão de ativos em diferentes períodos. Utilizamos uma base de dados única de preços de locação de escritórios comerciais sitos em São Paulo para criar dois tipos de indicadores baseados em dummy de tempo. Segundo nosso registros, não existem estudos sobre a recente desaceleração neste mercado ou que compare o desempenho de diferentes métodos de dummies de tempo. O primeiro modelo – 'padrão' – inclui dummies de tempo, dummies de região e características dos imóveis. O segundo modelo – efeitos fixos – é um modelo alternativo, em que consideramos dummies de tempo, características variáveis no tempo (idade) e efeitos fixos específicos dos imóveis. Esta última metodologia lida com heterogeneidade atemporal não observada. Nossos resultados sustentam a estratificação por região e por classe para explicar a performance de diferentes nichos. O modelo padrão é frequentemente viesado para cima, especialmente nas regiões em desenvolvimento e entre prédios de primeira linha, onde a oferta é mais flexível. Esta metodologia limita a nossa capacidade de controlar efeitos de localização além do nível regional. A rigidez das variáveis hedônicas atemporais não permite acomodar características específicas quando novos edifícios entram na amostra de forma não-aleatória.

Palavras-chave: Mercado de escritórios; Modelagem hedônica; Brasil

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Introduction

Research on economic indices is well established in the finance literature, especially when it comes to liquid investment opportunities, such as equity markets (i.e. Hull & McGroarty, 2014; Nardy, Fama, Guevara, & Mussa, 2015; Orsato, Garcia, Mendes-Da-Silva, Simonetti, & Monzoni, 2015). Yet, investors are also interested in aggregate measures of illiquid assets, such as commercial real estate (CRE) price and rent growth, as they provide a useful benchmark of financial performance and enables lenders to value collateral more accurately. While this literature is present in developed countries (i.e. An, Deng, Fisher, & Hu, 2016; Chegut, Eichholtz, & Rodrigues, 2013; Fuerst, Liu, & Lizieri, 2015), studies of CRE indices in emerging market are often bounded for two reasons (Gaiarsa, 2015). First, reliable data is unavailable to the broader public. Second, even when such data is available, it is difficult to find long time series to build reasonable econometric estimates. The lack of quantitative information; however, does not undermine the relevance of CRE as an alternative investment opportunity in large developing economies.

This study aims to investigate indicators available in the Brazilian market, assess their usefulness and limitations, and suggest improvements based on modern real estate literature. The paper advances the literature in two areas – an explanation and empirical assessment of how technically superior (and relatively easy-to-employ) indicators can contribute to performance measurement in the context of Brazil and a comparison of performance across different time-dummy methods.

Available real estate indicators often rely on strong premises due to narrow details on property attributes and location. Interpreting such indicators is usually difficult as they are computed from samples of properties that have unique characteristics. Comparisons of index values in different dates can be misleading, especially when the quality of properties available in the market is correlated with economic activity. For instance, greater index values may reflect sales of newer assets rather than an actual increase in the price of a standard property. This issue is exacerbated in the context of emerging market economies, where business cycles are typically more volatile than that of developed markets.

Data quality is also a concern in the context of emerging markets due to low transparency and illiquidity. Researchers from developed economies often recommend the use of transaction-based data to construct indices as they provide more timely information, especially in market turning points (i.e. Chegut et al., 2013; Fisher, Geltner, & Pollakowski, 2007; Geltner & Fisher, 2007). Such information; however, is often proprietary and search costs in public records are prohibitive. Registered documents generally do not contain detailed information on property attributes. In some countries, such as Brazil, many CRE deals are not necessarily registered because the cost of transacting special purpose entity (SPE) shares is lower than that regular property deal. Omitting such transactions from an index could create selection bias as SPE deals are often associated with larger properties. Munneke and Slade (2000, 2001) confirm the presence of sample selection bias on data from specific populations of office properties in the United States and report a relatively minor bias. This happens because properties transacted in each period are not necessarily representative of the whole market. Market illiquidity in developing countries could create large distortions in transaction-based measures.

Hedonic regressions are one way to overcome many of the limitations associated with median-price methods. They control for quality of the assets in place and the quality of the assets that are put on the market at different times. For office properties, the hedonic approach entails regressing rent or price values on a vector of property-specific and locational attributes. The coefficients represent the marginal value of these characteristics. Changes in these features can be accommodated in the estimates. A constant-quality indicator is then constructed by using the regression to impute a series of prices for a reference set of properties in each time-period. Albeit the theoretical appeal, hedonic regressions have not been widely used as they require detailed data on property features (i.e. Dorsey, Hu, Mayer, & Wang, 2010; Rappaport, 2007).

We use a unique appraisal-based dataset to create two types of hedonic measures for the city of Sao Paulo, the world's 5th largest urban agglomeration with 20.8 million inhabitants (United Nations, 2014), representing 11.5% of Brazil's GDP in 2011 (Instituto Brasileiro de Geografia e Estatistica, 2011). The data contains detailed characteristics from office properties that were available for rent between 2005:Q3 and 2014:Q3. The extensive data allows us to account for locational and temporal heterogeneity and construct quarterly indicators. We also consider different locational submarkets and building classes to compare their performance overtime. Many studies suggest that stratification can be a powerful tool for market analysis, yet this is not always considered by entities that create local indicators.

Dunse and Jones (2002) and Dunse, Leishman, and Watkins (2002) test whether city-level office markets, often assumed as a unitary market, can be divided as intra-metropolitan submarkets using data from Glasgow and Edinburgh. The authors conclude that the office market consists of a set of submarkets which are best defined upon real estate agent's views of market fragmentation as property attributes do not remain constant across different regions of these cities. Recent research from White and Ke (2014) validate that certain office submarkets, such as Pixi and Pudong, located in Shanghai, cannot be viewed as homogeneous or perfect substitutes as the authors do not find convergence in rental performance or interactions among these submarkets. Fuerst, Mcallister, and Sivitanides (2015) provide evidence of heterogeneous returns among building classes in the United States. These authors suggest that the price spread between top-tier and other office properties rose substantially during the financial turmoil of 2007–2009.

This research also contributes to the broader real estate literature as it compares the performance of two hedonic models directly derived from the time dummy method. The first is a quintessential hedonic model which includes locational submarket dummies, time dummies and property-specific attributes. The alternative model considers time dummies, time-varying characteristics (age) and property-level effects as covariates (An et al., 2016). This approach is appealing because it requires

less data on individual property features and avoids the pervasive omitted variable bias associated with standard hedonic regressions (Campbell, Giglio, & Pathak, 2011; Ghysels, Plazzi, Torous, & Valkanov, 2013; Hill, Melser, & Syed, 2009). We denominate these models *standard* and *fixed effect*, respectively. Many authors focus on developing robust hedonic methodologies (e.g. An et al., 2016; Dorsey et al., 2010; Hill et al., 2009), but rarely compare the performance of their models with that of more basic hedonic regressions. Hill et al. (2009) contrasted two hedonic methodologies using a large dataset from Sydney. These authors reported that imputation indices can increase more than time-dummy measures as the latter method fails to account for shifts in the shadow prices of characteristics, creating a bias analogous to substitution bias.

Motivated by the literature on aggregate measures of real estate financial performance, this paper explores three interrelated research questions. How useful in practice are commercial real estate indicators available in Brazil? How can superior (and easy-to-employ) indices contribute to performance measurement in emerging real estate markets? How do straight time-dummy indicators compare in terms of performance with fixed effects time-dummy indices?

This study is structured as follows. The subsequent section discusses the relevance of Brazilian indices for CRE investors and discusses certain methodological issues with these indicators. This is followed by a description of the dataset and its main variables. We then discuss the pros and cons of using appraisal-based data in the context of an emerging market economy. Next, identification strategies used to construct the hedonic-based measures are shown and empirical estimates are reported. Finally, conclusions are drawn.

The relevance of local indices for commercial real estate investors

Gaiarsa (2015) discussed the main advantages and disadvantages of three Brazilian indices: IGMI-C, FIPE-ZAP and IVG-R. We categorize some of the main issues associated with these aggregate measures, focusing on their relevance for real estate investors and on specific methodological caveats which could be useful to improve CRE indicators for emerging markets.

Among the three measures, the General Commercial Real Estate Index (IGMI-C), published by FGV/IBRE, is the only index that covers CRE properties in Brazil. The data is collected from large institutional investors and comprises all types of commercial real estate (i.e. shopping malls, industrial warehouses, commercial towers, parking, and hotels). The total return of each property "x" in the IGMI-C is broken in two components: net operating income and capital gains.

The index is appealing because the return figure considers total returns as well as a rigorous control for quality as it takes both investments and divestitures into account when computing performance. There are; however, two main caveats to the IGMI-C index. First, data is obtained from a limited number of institutional investors which do not necessarily represent the whole market. The index available to the public does not target specific regions or property-type segments. Second, variation in the IGMI-C may be generated by noisy changes in sample composition and size. One may question whether the proportion of each asset class remained homogeneous since inception, especially because in Q1:2000 the IGMI-C sample had 190 properties and 580 in Q4:2014.

The other two indicators, FIPE-ZAP, published through a partnership between Fundacao Instituto de Pesquisas Economicas (FIPE) and ZAP Imoveis (ZAP), and IVG-R, measured by the Brazilian Central Bank, rely on the median-price methodology. Both indices are appealing because there are relatively simple to be computed and interpreted. Nevertheless, the median-price methodology often ignores locational and physical attributes of properties in each market. In other words, they do not appropriately control for quality of the assets in place or the quality of the assets that are put on the market at different times. Not surprisingly, one may expect spurious fluctuations on median-price indices which are not necessarily related to local economic conditions.

Both measures partially circumvent this issue through stratification. The IVG-R keeps track of the value of the collateral for residential mortgage contracts in 11 major metropolitan regions in Brazil, aggregates the median value of these agreements for each city and is weighted according to the number of households of each area. The FIPE-ZAP keeps track of rent and prices of residential real estate properties in various metropolitan regions. The data is stratified according to the number of bedrooms, ranging from 1 to 4 or more, and to ponderation areas, which are specific locational strata of municipalities defined by IBGE based on socio-economic factors (FIPE-ZAP, 2014). Ponderation areas are then aggregated based on the Brazilian Demographic Census at metropolitan and national levels. Although FIPE-ZAP does a reasonable job at controlling for location, it has a limited capacity to disentangle time-varying physical attributes, such as age, at strata level.

The take away from this section is that CRE investors lack an aggregate measure that targets specific locations and property-type segments in Brazil. Moreover, the indicators available are prone to undesired fluctuations associated with unavailability of market-wide data (IGMI-C) and methodological caveats linked to stratification (FIPE-ZAP and IGV-R).

Methodology

Our approach to suggest improvements to existing indicators consists of three parts. First, we describe the dataset considered and the variables used to control for property-specific heterogeneity. Second, we highlight how stylized facts from emerging market data also affect real estate performance measurement. Finally, we specify two types of hedonic models and explain how they address some of these matters.

Dataset

The dataset was extracted from CRE Tool, a system which offers an extensive appraisal dataset for office properties located in various Brazilian cities. This system is provided by

Table 1
Definition of variables.

Income	The natural logarithm of nominal asked rent per square foot denominated in Brazilian Real (BRL).
Corporate	A dummy defining whether rental areas of a given property are small or large. Buildings defines these niches based on the average size of leasable units inside a given property and sets a cut-off threshold of 100 sqm. Properties above this number are considered *large* and the remainder *small*. This variable is set to one when an asset belongs to the first group at a given period and zero otherwise. The data provider, as is custom in the market (Colliers International, 2014; Credit Suisse, 2016), uses this variable to identify properties more likely to house large corporate tenants. We make no such distinction but include it as a locally appropriate control.
Rating	A property classification system developed by Buildings (standard categories AAA, AA, A, BB, B and C). The data provider classifies *Rating* based on objective (i.e. gross leasable area, floor area and age) and subjective (i.e. current occupation, corporate image and quality of technical specifications) characteristics of each asset. We converted this variable into a dummy to capture each building class (standard categories AAA, AA, A, BB, B and C). This variable is set to one when an asset belongs to a certain class at a given period and zero otherwise. All C class buildings were set to zero to avoid perfect collinearity. Thus, all other classes are measured as premiums relative to this class. Letter grade measures are often adopted by market practitioners as simplified proxy for of asset quality (Colliers International, 2014; Credit Suisse, 2016).
Age	Measured from the year of construction or the year of a major refurbishment, whichever occurred more recently. Observations for building age were segmented into thresholds to allow for potentially time-varying age effects. If a building belongs to a certain age group, this variable takes the value of one and zero otherwise. All properties that are less than 5 years old were set to zero to avoid perfect collinearity. Hence parameters for all age thresholds represent discounts relative to new assets.
Size	The natural logarithm of the gross leasable area measured in squared meters

Buildings,[1] a company solely specialized in real estate research. The CRE database from Buildings is the largest and perhaps the most detailed non-proprietary source of data for office properties in Brazil. Many institutional investors and real estate companies use this information to make investment decisions.

According to Buildings, all data from CRE Tool are collected from landlords, brokers and/or through visits in each property and is updated on a quarterly basis. The unbalanced panel dataset covers 20,562 property-period observations (1622 buildings) of Sao Paulo's office market from 2005:Q3 to 2014:Q3 on a quarterly basis.

The sample is divided in 14 locational submarkets and contains information about all the following characteristics for properties in these regions (Table 1).

Table 2 contains more information about the property classification system adopted by Buildings. Unfortunately, the data provider is unable to furnish further details. While this table sheds some light on the objective criteria, it would have been useful to understand the methodology behind the subjective criteria. Technical specifications, corporate image and occupation profile are useful information for real estate investors. Nevertheless, some of these variables are qualitative in nature and there are many details to be considered due to the heterogeneous nature of CRE properties. An interesting feature of this classification system is that it does not take location into account.

The 14 locational submarkets considered as controls in our estimates are Barra Funda, Berrini, Centro, Chacara Santo Antonio, Faria Lima/Itaim Bibi, Marginal Pinheiros, Moema/Vila Mariana, Morumbi/Jardim São Luiz, Paulista, Pinheiros/Perdizes, Santo Amaro, Saude/Jabaquara, Vila Olimpia and other. These regions are in the heart of the city of Sao Paulo and are viewed by practitioners as the most relevant office locations (see, for instance, Colliers International, 2014). Other, potentially less relevant submarket areas, are not covered in this study (Fig. 1).

Data issues in emerging markets

Before we proceed to the empirical section, it is important to understand the appeals and limitations of our dataset. Asking rent is an appraisal-based measure of return and, thus, subject to measurement error. The literature shows that measurement error in appraisal-based indices comes from temporal lag bias and valuation smoothing (e.g. Fisher, Geltner, & Webb, 1994; Geltner & Fisher, 2007; Geltner, 1993a, 1993b).

Temporal lag bias arises when multiple valuations are pooled together in one period to improve index precision. This type of error is primarily applicable to indices that group property price appraisals over long time intervals. This is not a large concern in our dataset as the provider aggregates and reviews asking rent figures on a quarterly basis. Valuation smoothing can arise for multiple reasons. Lai and Wang (1998) and Crosby, Devaney, Lizieri, and Mcallister (2015) find that appraisers might have incentives to smooth valuations due to "exogenous" pressures, such as meeting a corporate hurdle rate. This issue can be exacerbated in the context of emerging markets due to lack of transparency.

Fuerst (2008) argues that the spread between asking and actual rents tends to be larger in peaks and troughs. For instance, landlords usually provide discounts and other incentives to tenants in recessionary periods instead of lowering asking rents. Cho, Hwang, and Lee (2014) use time-varying asset pricing models to find that appraisal smoothing is on average close to zero, but changes substantially overtime.

One logical alternative to appraisal-based indices would be to use transaction-based measures. Fisher et al. (2007), Geltner and Fisher (2007), Chegut et al. (2013) and Gaiarsa (2015) document that the latter provides more timely information, especially in market turning points. Gaiarsa (2015) reports similar results in the context of Brazil by comparing the performance of the IVG-R and FIPE-ZAP indices. These indices rely on transactional- and appraisal-based measures of residential properties, respectively.

[1] For more details regarding Buildings, please visit their website: http://www.buildings.com.br.

Table 2
Details of the property classification system in the baseline dataset.

Macro classification		A		B		C	
Micro classification		AAA	AA	A	BB	B	C
Objective criteria	Floor plate area (sqm)	≥1500	≥1000	≥500	≥500	≥250	N/A
	Gross leasable area (sqm)	≥20,000	≥10,000	≥5000	≥5000	≥2500	N/A
	Age (deliver/retrofit)	≤20 years		≤40 years		N/A	
Subjective criteria (grades)	Sum of grades	≥13	≥11	≥8	≥5	≥5	≥3
	Technical specifications	1–5	1–5	1–5	1–5	1–5	1–5
	Corporate image	1–5	1–5	1–5	1–5	1–5	1–5
	Occupation profile	1–5	1–5	1–5	1–5	1–5	1–5

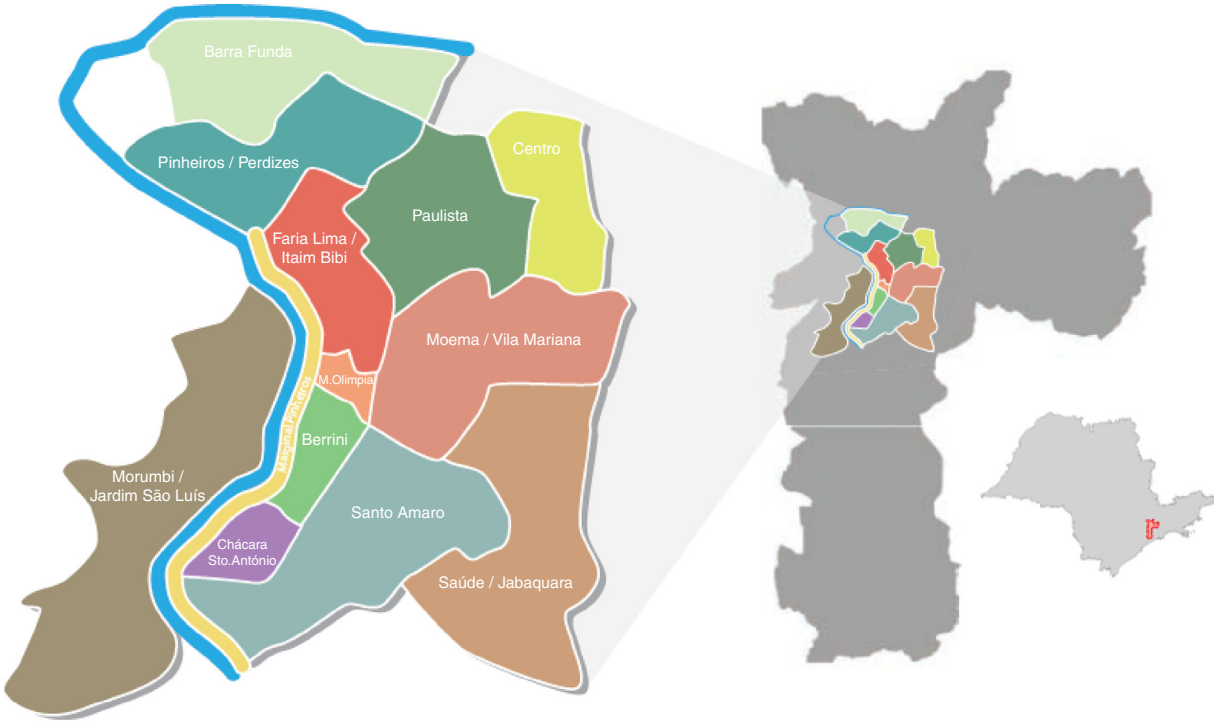

Fig. 1. Locational submarkets in the dataset.

Albeit the drawbacks of using asking rent in this study, transactional-based figures also have features which limit our ability to study them in detail. First, aggregate transaction data on CRE is nearly absent in the context of emerging markets. This information is often proprietary and search costs in public records are large. Second, even if appraisals are not the best tool to detect market fluctuations, "the appraisal is the foundation of real estate valuation and decision making. It is a trusted part of the transaction process, can be frequently updated and is an alternative when transaction or data environments are dry" (Chegut et al., 2013, p. 589). Finally, it is often difficult to understand the nature of the deals or to obtain sufficient details on property attributes in registered transaction documents.

Many transactions occur for reasons that not tied to typical supply and demand conditions. Campbell et al. (2011), for instance, show that forced-sale of houses in Massachusetts carry a 28% discount on regular sales prices. Sale-and-lease back (SLB) deals, in which the seller leases back the property from the buyer, are often associated with the seller's capacity to repay rent and inability to tap external financing. This is particularly relevant in CRE markets, where SLB transactions provide an alternative source of funding to the seller.

Moreover, public records do not necessarily register all the deals. CRE properties are sometimes inserted into special purpose entities (SPE) and then transacted as a purchase of shares. In this case, the seller trades the SPE shares with the buyer, but there is no registered transfer of ownership on the underlying asset (i.e. the SPE remains the owner). This type of deal became increasingly popular in some countries as the cost of transacting SPE shares is lower than transacting CRE directly.

It would have been ideal to contrast the empirical results, where we consider asking rent as a dependent variable, with those of actual rents for robustness. Nevertheless, the unavailability of information on lease transactions limits our capacity to do so. This is a potential opportunity for future research when the required data is available.

Identification strategy

We stratify the data based on selected *locational submarkets* or *building classes* to estimate log linear time dummy models as in Fuerst, Liu, et al. (2015). Stratification allows us to adjust for distinct valuation of characteristics in these submarkets as suggested in the previous sections. The model takes the following form:

$$P_{imt} = \beta_c C_{ci} + \tau_t Q_{it} + \alpha_m Q_{im} + e_{imt} \quad (1)$$

where P_{it} is the natural logarithm of asking rent per square meter of property "i" located in submarket "m" at time "t" and C_{ci} is a vector of "c" observable hedonic attributes of property "i" as defined in Tables 1 and 3. The term Q_{it}, is an $T*(Q_{it}-1)$ matrix of dummy variables, τ_t is a $(Q_{it}-1)*1$ vector of period parameters and Q_t is the number of quarters. The term Q_{im}, is an $M*(Q_{im}-1)$ matrix of dummy variables, α_m is a $(Q_{im}-1)*1$ vector of submarket parameters and Q_m is the number of regions defined by Buildings. We set $Q_{it}\,\forall\, t=1$ equal to zero so that τ_t captures a logarithmic approximation of the property-type rental index relative to the first period.

Following An et al. (2016), we test an alternative model with property-level identifiers. Hill et al. (2009), Campbell et al. (2011) and Ghysels et al. (2013) suggest that there may be still a concern with unobserved heterogeneity, both locational and property-specific, in standard hedonic models. Adding narrower fixed effects may correct for this potential bias and improve the predictive power of hedonic models (Hill et al., 2009). This approach is also appealing because it requires less data on individual property features. The alternative model is as follows:

$$P_{imt} = \beta_c C_{cit} + \tau_t Q_{it} + \alpha_i + e_{imt} \quad (2)$$

The term α_i represents the fixed effects identifiers. Note that time-unvarying characteristics, such as size, are dropped as they are perfectly collinear with α_i. For this reason, we only consider a vector of time-varying characteristics C_{cit} in the alternative model. An et al. (2016) adopt a similar specification and separate age from property-specific features that tend to stay more constant overtime.

For both models, the office rental index r_t for period "t" is obtained through exponentiation of the estimated time dummy $\hat{\tau}_t$.

$$r_t = \exp(\hat{\tau}_t) \quad (3)$$

These regression-based models deal with the methodological caveats linked to median-price stratification because they control for both locational and property-specific heterogeneity. The empirical estimates; however, use *asking* rent and are prone to critiques associated with valuation smoothing. This may restrain comparisons between rent dynamics across different locations and building-classes due to measurement error in market turning points. Unfortunately, we do not have access to *actual* rents to construct a transaction-based measure.

Results

Tables 3 and 4 report estimated property features of Eqs. (1) and (2) for the entire sample, selected locational submarkets and building class segments. Fig. 2 shows regression output for the quarter dummies. The locational strata consider value submarkets (Faria Lima/Itaim and Paulista), growth regions (Vila Olimpia, Berrini, Marginal Pinheiros and Chacara Santo Antonio) and Centro (Colliers International, 2014). We also measure performance among higher-end (AAA, AA, A and BB-rated) and lower-tier (B and C-rated) subsamples of properties.[2] Eqs. (1) and (2) shall be defined as *standard* and *fixed effect* models henceforth. Standard errors in all estimates are robust as in White (1980).

To estimate *Income* for *standard*, we used all variables from the baseline dataset, namely *Age, Rating, Corporate* and *Size*, as defined in Table 1, and, where applicable, locational submarkets. The submarket dummies were excluded from *standard* model in regression (IV), which only considers Centro submarket. The implicit assumption of the *standard* model is that the submarkets considered are homogeneously similar in term of locational quality.

The *fixed effect* model includes the property identifiers and *Age*, as suggested by An et al. (2016). The covariates *Rating, Size* and the submarket dummies were excluded from Eq. (2) because they do not vary substantially overtime. In addition to specific locational attributes, the property effects identifiers capture all average cross-sectional variation linked to building-specific heterogeneity. Thus, the interpretation of parameters related to time-varying property characteristics becomes less intuitive in the *fixed effect* model than in the *standard* model.

Regressions (I) through (VI) report the estimates of the *standard* model. Most property-specific features are significant, which is coherent with literature on determinants of office rent (e.g. Eichholtz, Kok, & Quigley, 2010; Fuerst & McAllister, 2011; Reichardt, Fuerst, Rottke, & Zietz, 2012; Slade, 2000). These figures suggest that median-price measures are not appropriate when property quality varies considerably from one period to the other.

Valuation of property-specific features also varies among different regions and building classes. These results are consistent with those of Dunse and Jones (2002) and Dunse et al. (2002) and suggest that Sao Paulo's office properties cannot be viewed as unitary market. For instance, regressions (III) and (IV) indicate that *Age*, *Corporate* and *Size* play a more important role on rent pricing in value submarkets than in Centro. This difference can be explained by the larger concentration of banks and corporate headquarters in value locations. Most properties in Centro are obsolete and occupied by liberal professionals. Organizational structure, size and opportunistic behavior may lead different users to value locations unalike (Clapp, 1993).

[2] These broader expert-based definitions were employed for simplicity, but granular analysis for each specific region or building category could also be considered.

Table 3
Standard regression estimates of ln(Income/sqm) – property characteristics.

Strata/independent variables	(I) Total sample	(II) Growth submarkets	(III) Value submarkets	(IV) Centro submarket	(V) High rated properties	(VI) Low rated properties
Size	0.107***	0.050***	0.184***	0.084***	0.099***	0.104***
	(18.33)	(3.85)	(19.59)	(7.93)	(10.35)	(15.46)
Rating						
AAA	0.280***	0.408***	0.127***		0.203***	
	(12.41)	(11.25)	(3.02)		(7.88)	
AA	0.317***	0.377***	0.254***		0.229***	
	(16.33)	(12.35)	(9.49)		(10.68)	
A	0.182***	0.256***	0.166***	0.190*	0.110***	
	(16.01)	(12.26)	(8.87)	(1.65)	(6.34)	
BB	0.129***	0.217***	0.059***	0.174***		
	(10.42)	(9.42)	(3.04)	(4.73)		
B	0.034***	0.109***	−0.005	−0.061**		0.038***
	(5.40)	(7.91)	(−0.48)	(−2.32)		(5.73)
Corporate	0.120***	0.168***	0.189***	−0.053***	0.316***	0.083***
	(20.54)	(17.08)	(22.20)	(−3.44)	(28.73)	(12.54)
Age (yrs)						
5 to 9	−0.084***	−0.074***	−0.090***	0.143	−0.091***	−0.125***
	(−10.93)	(−6.58)	(−7.15)	(1.23)	(−8.27)	(−12.89)
10 to 14	−0.208***	−0.186***	−0.229***	−0.105	−0.159***	−0.256***
	(−26.82)	(−15.85)	(−18.85)	(−0.84)	(−13.92)	(−26.62)
15 to 19	−0.314***	−0.316***	−0.294***	−0.361***	−0.294***	−0.354***
	(−36.98)	(−24.13)	(−21.02)	(−3.03)	(−18.52)	(−34.41)
20 to 24	−0.372***	−0.454***	−0.341***	−0.265**	−0.389***	−0.396***
	(−35.40)	(−26.25)	(−22.12)	(−2.37)	(−17.27)	(−32.35)
25 to 29	−0.464***	−0.460***	−0.462***	−0.461***	−0.419***	−0.484***
	(−38.99)	(−25.32)	(−26.55)	(−4.17)	(−17.39)	(−34.97)
30+	−0.535***	−0.533***	−0.519***	−0.625***	−0.470***	−0.555***
	(−54.81)	(−24.54)	(−41.45)	(−5.80)	(−21.18)	(−48.56)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Submarket dummies	Yes	Yes	Yes	No	Yes	Yes
Property fixed effects	No	No	No	No	No	No
Observations	20,566	4491	7701	3429	3822	16,744
R-squared	0.78	0.80	0.75	0.51	0.86	0.75
Number of properties	1622	338	621	240	333	1315

This table reports selected parameters and white robust standard errors of property characteristics. Where applicable, these coefficients are stratified estimates of Eq. (1), "Standard". The variables considered are specified in Table 1. The data covers commercial towers from the city of Sao Paulo from 2005:Q3 to 2014:Q3. The locations used as strata or submarket dummies are specified in Fig. 1. Stata 13 statistical package was used to compute these estimates. Indexes *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, and t-statistics are reported in parentheses.

Heterogeneous pricing of similar characteristics is also true when we stratify the sample based on building classes. Regressions (V) and (VI) show that the correlation between physical depreciation and rent is larger among low-tier properties. One possible explanation for this outcome is that top-tier properties have better maintenance as they are typically owned by a single investor. Bischoff and Maennig (2011) indicate that certain building characteristics are important determinants of landlord segmentation.

Fig. 2 compares the time dummy coefficients of the *standard* and *fixed effect* models in the third quarter of each year. Both methodologies indicate statistically similar outcomes in most cases, except in growth submarkets and among higher-end properties. Without recurring to standard errors, the *fixed effect* model yields lower rent growth figures in all models. These results suggest that the logarithmic approximation of the quarter dummies is *generally* not sensible to the type of model adopted. The differences; however, increase as we convert the logarithmic approximations into percent changes.

Fig. 3 reports inflation-adjusted quarterly rent indices for the city of Sao Paulo. The *standard* and *fixed effect* quarter dummies were converted into actual percent changes and then deflated in each period by the cumulative inflation (Indice Geral de Precos de Mercado – IGP-M) of 2005:Q3. The resulting appraisal-based measures may be subject to valuation smoothing; however, they do reflect to some extent the cyclicality of rent. Between 2005 and 2008, office markets have experienced a full growth cycle due to a strong economic environment. In 2009:Q3 rent grew at a slower pace in the aftermath of the global financial crisis and started to recover in 2010:Q3, when economic activity rebounded and interest rates were very low. From 2013:Q1 onwards, office rent prices stagnated – and even declined – as the Brazil entered in a recession.

Another set of trends appears when we compare the stratified indicators based on locational submarkets. Both *standard* and

Table 4
Fixed effect regression estimates of ln(Income/sqm) – property characteristics.

Strata/independent variables	(VII) Total sample	(VIII) Growth submarkets	(IX) Value submarkets	(X) Centro submarket	(XI) High rated properties	(XII) Low rated properties
Age (yrs)						
5 to 9	−0.123***	−0.072***	−0.114***		−0.118***	−0.110***
	(−7.05)	(−3.35)	(−4.81)		(−4.52)	(−5.00)
10 to 14	−0.217***	−0.094***	−0.230***	0.074	−0.150***	−0.207***
	(−8.21)	(−2.77)	(−6.89)	(0.59)	(−3.47)	(−6.96)
15 to 19	−0.258***	−0.113**	−0.229***	0.017	−0.247***	−0.236***
	(−7.44)	(−2.41)	(−4.99)	(0.12)	(−4.00)	(−6.35)
20 to 24	−0.292***	−0.105*	−0.227***	−0.071	−0.329***	−0.243***
	(−5.80)	(−1.65)	(−3.71)	(−0.48)	(−3.96)	(−5.08)
25 to 29	−0.312***	0.058	−0.272***	−0.250	−0.297***	−0.242***
	(−4.09)	(0.75)	(−3.84)	(−1.35)	(−2.87)	(−4.04)
30+	−0.320***	0.119	−0.290***	−0.150	−0.260**	−0.234***
	(−3.31)	(1.27)	(−3.43)	(−0.77)	(−2.12)	(−3.35)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Submarket dummies	No	No	No	No	No	No
Property fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,566	4491	7701	3429	3822	16,744
R-squared	0.7097	0.7825	0.7702	0.5843	0.7626	0.7057
Number of properties	1622	338	621	240	333	1315

This table reports selected parameters and white robust standard errors of property characteristics. Where applicable, these coefficients are stratified estimates of Eq. (1), "Standard". The variables considered are specified in Table 1. The data covers commercial towers from the city of Sao Paulo from 2005:Q3 to 2014:Q3. The locations used as strata or submarket dummies are specified in Fig. 1. Stata 13 statistical package was used to compute these estimates. Indexes *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, and t-statistics are reported in parentheses.

fixed effect rent indices show that value regions slightly outperformed and were less volatile than the city-wide index. These are well established office regions and demand for space in these locations is generally strong.

Standard and *fixed effect* results vary considerably when we consider growth submarkets. The *standard* model shows that these regions rose in line with the city-wide indicator until 2012:Q2 and then underperformed the benchmark. The *fixed effect* model shows that performance in these locations was in most cases lower than that of the city-wide index, especially after 2012:Q1. Albeit these differences, both indicators suggest that emerging office locations suffered the largest rent devaluation during the current recession.

Growth regions are the most susceptible to unobserved heterogeneity linked to locational quality in the *standard* model. A large proportion of office development activity was concentrated in these locations during the period analyzed. One of the key differences between the two methodologies is that the *standard* model considers region-specific effects, whereas the *fixed effect* approach deals with locational heterogeneity directly at property level. Hence, adding a building located in a better-than-average area (i.e. an important avenue) to the sample biases the *standard* indicator upwards. Put differently, the assumption of randomness at submarket level is insufficient to capture the effect of properties being quoted in better/worse locations *within* these submarkets at different times. Part of locational quality is thus soaked by the time dummy, creating the bias. An et al. (2016) report that the use of median-price methods, which also fail to account for unobserved heterogeneity, also yield an overestimation of long-term rental growth.

When we turn our attention to stratified indicators linked to building classes, we also observe "over performance" of *standard* estimates among top-tier properties. The gap between this measure and the *fixed effect* indicator widened in the boom period following the financial crisis of 2009 and then curtailed as the market approached the recession (Fig. 2). This outcome suggests that our time-unvarying hedonics were too rigid to accommodate better-than average quality of new properties in boom periods (Slade, 2000). Robust measures should not change in response to non-random observations added to the sample in expansionary markets. This outcome is reinforced by the homogeneous performance of both methodologies among low-tier buildings, which have a relatively rigid supply.

Another result which may be considered for future research is the poorer performance of quoted top-tier properties throughout the recent recession. This result contradicts the "flight-to-quality" movement proposed by Fuerst, Mcallister, et al. (2015). These authors use a transaction-based dataset from the US and show that the spread across building classes increases in recessionary periods. Based on these results, we would normally expect rent from low-tier properties to decrease more than that of higher end office buildings. Ibanez and Pennington-Cross (2013) estimate asking rent dynamics for US office properties and find that class A assets properties adjust back to equilibrium faster than their peers, possibly because occupiers are different across quality spectrums.

Conclusions and final remarks

This research explains how certain limitations affect the usefulness of real estate indices available in Brazil and how

Fig. 2. Regression estimates of ln(Income/sqm) – selected quarter dummies. This figure reports selected parameters and white robust standard errors of selected time dummies. Where applicable, these coefficients are stratified estimates of Eqs. Eqs. (1) – "Standard" and (2) – "Fixed Effect". The variables considered are specified in Table 1. The data covers commercial towers from the city of Sao Paulo from 2005:Q3 to 2014:Q3. The locational submarkets and are defined in Fig. 1. Stata 13 statistical package was used to compute these estimates.

specialized, technically superior (and relatively easy-to employ), indices can contribute to improve performance measurement in the context of emerging markets. To do this, we use a large appraisal-based rent dataset from Sao Paulo's office market to create stratified hedonic-based measures for office properties. Hedonic techniques are more rigorous than median-price measures to control for quality of the assets in place or the quality of the assets that are put on the market at different times. This is particularly relevant in economies with pronounced economic cycles. To our records, there appears to be no studies that cover the recent meltdown in this market in such level of detail.

The paper also contributes to the broader real estate literature are we compare aggregate measures derived from two hedonic models based on the time dummy method. The first is a quintessential hedonic model which includes locational submarket dummies, time dummies and property-specific attributes. The second is an alternative model, like that of An et al. (2016), in which we include time dummies, time-varying characteristics and property fixed effects. The appeal of this methodology is that requires less data on hedonic features and avoids the pervasive omitted variable bias linked to quintessential hedonic regressions (Campbell et al., 2011; Ghysels et al., 2013; Hill et al., 2009). We denominate these models *standard* and *fixed effect*, respectively.

The resulting indices reflect to some extent the cyclicality of rent. Consistent with market segmentation theory, our findings favor locational and building class stratification to consider heterogeneous performance in these niches. The *standard* model can be upward biased, especially among growth submarkets and top-tier properties, where supply is more flexible due to larger

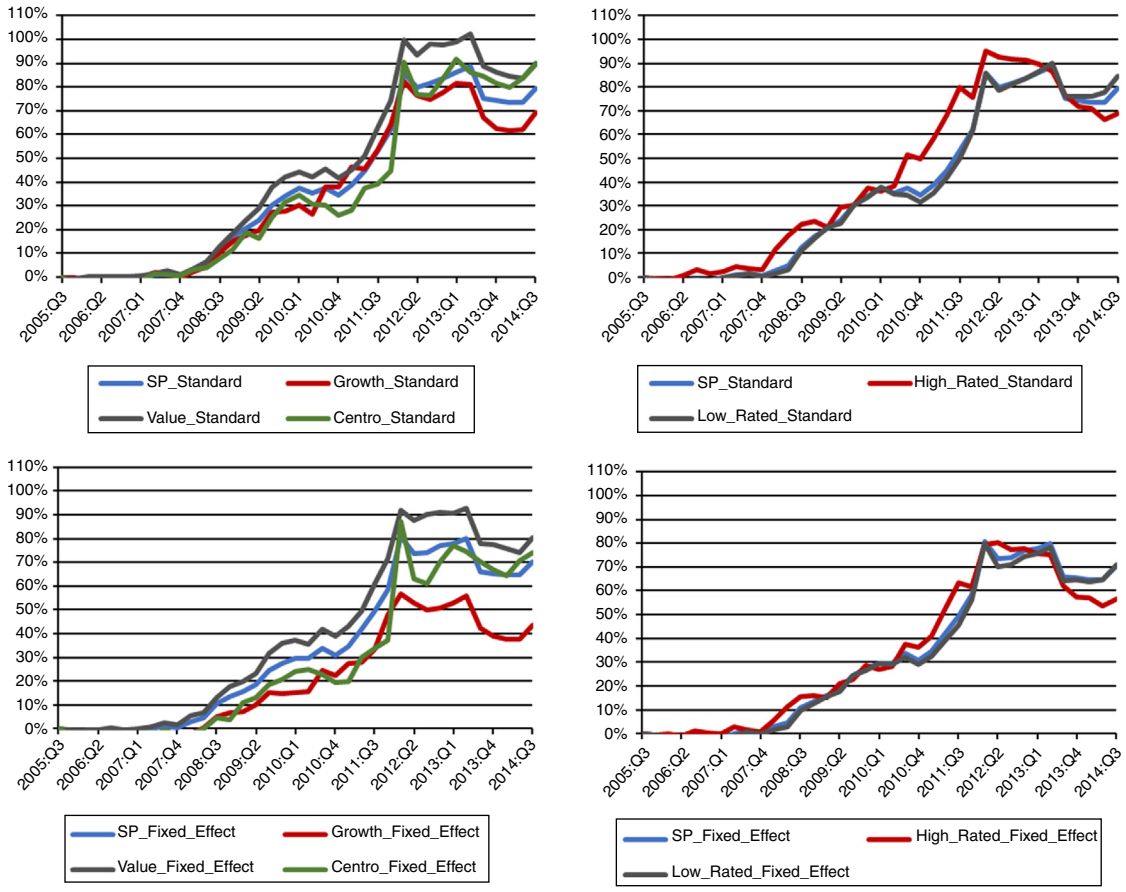

Fig. 3. Sao Paulo quarterly rental price indices – constant prices (set/2005 = 0). This figure reports stratified quarterly rental indices derived from the time dummy coefficients of Eqs. Eqs. (1) – "Standard" – and (2) – "Fixed Effect". These indicators were deflated by the cumulative Indice Geral de Precos de Mercado (IGP-M) of 2005:Q3. The data covers commercial towers in the city of Sao Paulo from 2005:Q3 to 2014:Q3. The selected submarkets used as strata are specified in Fig. 1.

development activity. The randomness assumption embedded in the *standard* model fails to capture the effect of properties in better-than-average locations *within* submarket level. Furthermore, time-unvarying hedonics averaged across existing buildings may be too rigid to isolate the impact of top-tier properties added to the sample in boom periods (Slade, 2000). These results reinforce that obtuse measures available often fail to disentangle specific aspects of real estate cycles, which tend to be quite prominent in emerging real estate markets.

The lack of historical data, especially transaction-based, limits our ability to further examine the nature of these microeconomic discrepancies in performance and whether these gaps would remain steady in the long-run. This issue will have to be addressed as data availability as well as the level of detail and accuracy improve over time.

Conflicts of interest

The authors declare no conflicts of interest.

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